RECOMMENDER SYSTEM OF CONDUCTIVE INK OF PRINTED ELECTRONICS APPLICATIONS USING DEEP NEURAL NETWORKS

SYNOPSIS

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1. INTRODUCTION

For over six decades, electronic devices have been manufactured through a complex process involving photolithographic and chemical technique. These methods have been instrumental in creating intricate electronic circuits primarily on silicon or semiconductor materials. However, a paradigm shift in electronics manufacturing has emerged with the advent of Printed Electronics (PE) technology. Unlike traditional methods, PE uses standard graphic arts printing techniques to create diverse electronic devices by forming conductive traces on a typically organic and flexible substrate. PE technology allows to deposit different types of materials on a wide range of substrates by various printing techniques. The main purpose is to manufacture state-of-art electronic devices. Beyond the realms of printing and electronics, PE is a multidisciplinary domain, merging material science, chemistry, physics, reliability engineering, and wireless communication [1]. PE is one of the most booming technologies rising up these days [2]. According to the IDTechEx report 2019-2029 [3], the market value of the whole industry will be more than $7.6 billion by 2027 and expected to increase in the upcoming decade.

PE has gained significant attention in the industrial sector owing to its remarkable capability to fabricate electrical and photonic devices using innovative printing techniques like inkjet and screen printing coupled with conductive inks. The rapid expansion of PE and its widespread application across diverse sectors highlight its inherent potential to manufacture components with intricate features. In the realm of PE, conductive ink selection is a crucial process that directly shapes the quality of the final product. The use of appropriate conductive ink is essential for printing flexible electronic circuits, improving communicative functionalities of objects, and ensuring overall product quality. Consequently, selecting the right conductive ink is crucial to meet consumer requirements and ensure the competitiveness of products in the market. The conventional approach to conductive ink selection has been manual, labor -intensive, and time-consuming, relying on the expertise of designers. This approach inefficient and often leads to suboptimal material choices. Hence, there is a demand to design an automated system for conductive ink selection to overcome the limitations associated with manual processes.

The prime objective of this research work is to build automated systems for conductive ink selection in PE. The work focus of automated system design using neural network, metaheuristic algorithm, and deep learning approach.

2. LITERATURE SURVEY

Htwe and Mariatti [4] focused on conductive ink and its hybrid with other materials. The authors offered a summary of prior research on formulating conductive inks and their applications in PE. They also comprehensively reviewed various printing methods employed for depositing conductive inks and explored diverse post-printing techniques to improve performance. Rama et al. [5] discussed the process of conductive inks preparation and their applications on PE and flexible electronics. It is showed that the chemical methods for synthesizing silver ink.

Yao et al. [6] introduced a hybrid technique that combines Hierarchical Clustering (HC) and Support Vector Machine (SVM) for design feature recommendation. In this approach, HC was used for categorizing design features, while SVM improved the categorization outcome to detect suitable design features for car components. However, this approach may have limitations in handling large datasets or complex design spaces, as HC could struggle with high-dimensional data and SVM might require extensive tuning for optimal performance.

Droplet generation in printing could affect the printing accuracy. To solve such as issue, a ML model named Learning-Based Cell Injection Control (LCIC) was introduced by Shi et al. [7]. The LCICI model involved a computational fluid dynamics simulation model of a piezoelectric print-head, which considered the inverse piezoelectric effect. A Multilayer Perceptron (MLP) was designed and trained using simulated data. This trained MLP was then employed to automatically optimize printing parameters based on its classification performance. Results demonstrated that the MLP approach significantly improved printing efficiency.

Wu and Xu [8] employed NN for predicting drop speed and ink volume. The NN model was trained to predict drop speed and ink volume based on three input features such as voltage, rise time, and pulse duration. However, the model requires extensive training data to capture the full range of printing conditions and potential inaccuracies in predicting highly dynamic inkjet behaviors. Guo et al. [9] investigated how various factors affect the ejection volume of printing using ML algorithm. Authors focused on ink properties and process parameters to

understand their impact on the printing process. Experiments were conducted using different types of inks and varied process parameters such as voltage, nozzle diameter, and distance between the nozzle and the substrate. Results showed that the changes in process parameters and substrate influenced ejection volume with higher voltage and shorted distances leading to larger droplet volumes.

A novel method based on Machine Learning (ML) algorithm for optimizing droplet speed was described by Shi et al. [10]. Authors attempted to improve the bio-printing process by utilizing Fully Connected Neural Network (FCNN) to optimize multiple objectives simultaneously. This included enhancing printing speed, accuracy, and material usage efficiency. Kim et al. [11] presented an approach to optimize the drive waveform for inkjet printing, which was crucial for ensuring reliable printing based on the fluid properties of the ink. Authors used different types of inks, and each ink was jetted using various waveform designs. They evaluated and compared five ML models such as SVM, K-Nearest Neighbor (KNN), Random Forest (RF), MLP, and Extreme Gradient Boosting (XGBoost) to predict the jetting behavior characteristics. MLP showed the highest prediction accuracy among the different ML models.

Brishty et al. [12] explored the potential of ML algorithms in classifying ink and printer parameters based on jetting regime. They compared three ML algorithms including K- Nearest Neighbor (KNN), Decision Tree (DT), and Neural Network (NN). Performance the ML algorithms was compared. Results proved that the NN classifier achieved higher accuracy than KNN and DT classifiers. Drawbacks of this study could include the need for significant computational resources when dealing with large volume of data and the possibility of overfitting when utilizing NN models.

Chen et al. [13] created a prediction model based on Random Forest (RF) to accurately predict ejection cycle time and droplet size using experimental data obtained under various printing parameters. The prediction performance of the RF was contrasted against other ML approaches, including Classification and Regression Tree (CART), Support Vector Regression (SVR), and Artificial Neural Network (ANN). Results revealed that the RF model offered an efficient method to simultaneously predict ejection cycle time and droplet diameter, contributing to the advancement of printing toward accurate printing.

3. PROBLEM DEFINITION

Despite the growing importance of PE in various industries, the current approaches to conductive ink selection remains manual and inefficient. These conventional methods heavily rely on human expertise, not scalable and often prone to errors. This reliance on manual processes not only slows down the technological advancement but also constraints the potential capabilities of products derived from PE. The absence of automated tools for conductive ink selection creates a significant gap in the field, limiting the capabilities of printed electronics products. This gap underscores the critical need for the development of an automated system specifically designed to streamline and enhance the processes involved in conductive ink selection for PE applications.

To address this gap, the research proposes the design of automated systems for conductive ink selection. This advancement is not only essential for meeting the ever-evolving demands of consumers but also plays a crucial role in ensuring the high quality and reliability of PE products.

4. OBJECTIVES OF THE RESEARCH

The key objectives of the research work can be summarized as follows:

- To build a system for selecting conductive ink in printed electronics through the utilization of a Multilayer Perceptron Neural Network (MLPNN) and Support Vector Machine (SVM)
- To design a model for the selection conductive ink in printed electronics by integrating MLPNN with a Particle Swarm Optimization (PSO) algorithm
- To construct a model for conductive ink selection in printed electronics using a deep learning approach

5. RESEARCH METHODOLOGIES

In the field of PE, the selection of input and output variables for conductive ink selection play a crucial role in determining the success and efficiency of the printing process. The rationale behind choosing specific input and output variables lies in their direct impact on the performance and functionality of the PE. In this research work, the following input variables such as (i) Product life (1- 5), (ii) Product quality (1-5) (iii) Product usage and handling (1-5)

(iv) Grams per Square Meter (GSM) (0-200gsm) (v) Caliper/thickness (0-500mm) (vi) Brightness (0-100%) (vii)Tear resistance (0-200mN) and (viii) Moisture content (0-150gm/m2), and output variables including (i) Silver ink, (ii)Copper ink, and (iii)Carbon ink. The proposed systems have been implemented using image processing toolbox, neural network toolbox, and deep learning toolbox of MATLAB 2022a, released by Mathworks, Inc. The computational tasks were efficiently handled by an Intel Core i5 processor operating at 3.6GHz with 16GB RAM.

5.1. Automated Ink Selection System employing Artificial Neural Network for PE Applications

In the first phase of research work, an automated system is designed to choose conductive ink for PE applications using SVM [14] and MLPNN [15]. The developed system has four major phases. Primarily, input data is standardized to a uniform range of 0 to 1 using min-max method. Secondarily, the normalized data is split into training and testing sets. Training set is used to train a model, while test set is used to validate the model. Thirdly, two models such as MLPNN and SVM are developed and trained independently to capture the intricate relationship between input and output variables. Finally, these trained models are then employed to determine the suitable ink based on the test data. The effectiveness of these models is assessed by computing some widely used metrics such as accuracy, recall, precision, F1-score, Balanced Classification Rate (BCR), and Miss Classification Rate (MCR). Performance of the models are compared to determine the most effective network for conductive ink selection task.

5.2. Optimized Neural Network for Ink Selection in PE Applications

In this second phase of research work, a novel method is introduced to select conductive ink for PE using the power of PSO in conjunction with MLPNN. In this system, input data undergoes preprocessing via min-max method to ensure standardized input ranges. Subsequently, the standardized data is divided into training and testing sets. Next, MLPNN is designed and trained using PSO algorithm to effectively learn the hidden relation between input and output variables. Finally, the trained PSO-MLPNN is used to select ink based on input features. Similar to first phase, performance of the PSO-MLPNN system is thoroughly analysed by varying parameters. Additionally, a comparative analysis against the standard MLPNN is done to ascertain the strength and enhancements gained through the integration of PSO with MLPNN.

5.3. Deep Learning Model for Ink Selection in PE

In this phase of research work, an automated system to choose conductive ink using 1D Convolutional Neural Network (1D CNN) is designed. To ensure normalized input ranges and facilitate effective learning, the input data is preprocessed using min-max technique. The data is partitioned into training and testing data. A 1D CNN is designed and trained with the objective of optimizing conductive ink selection for PE applications. The efficacy of this system is evaluated through a comprehensive set of metrics. A comparative analysis against established systems such as SVM, MLPNN, and PSO-MLPNN is conducted.

6. EXPERIMENTAL RESULTS AND DISCUSSIONS

The efficacy of the introduced systems has been evaluated by assessing various metrics, including recall, precision, F1-score, BCR, MCR, and accuracy.

Where, TP-True Positive, TN-True Negative, FP-False Positive, and TN-False Negative. Table.1 summarizes the efficacy of the developed systems for choosing conductive ink for PE applications. It is observed that the deep learning model outperformed the SVM, MLPNN, and PSO-MLPNN across all metrics.

TABLE.1 PERFORMANCE OF THE DEVELOPED AUTOMATED SYSTEMS

Models	Accuracy (%)	Recall (%)	Precision (%)	F1 score (%)	BCR (%)	MCR
SVM	90.29	91.43	81.22	86.02	84.43	9.90
MLPNN	91.67	95	92.68	93.83	90.15	8.33
PSO-MLPNN	97.71	97.71	92.93	94.74	97	3.24
1D CNN	98.48	98.86	96.65	97.74	98.57	1.52

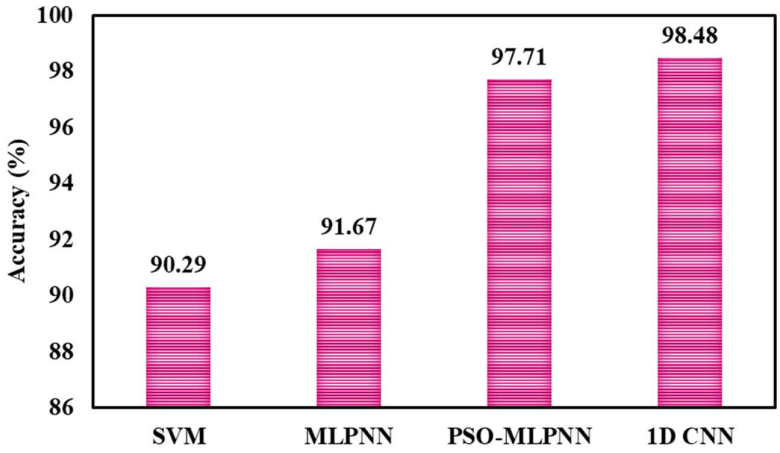

FIGURE.1 PERFORMANCE COMPARISON IN TERMS OF ACCURACY

Figure .1 graphically compares the performance of the developed models such as SVM, MLPNN, PSO-MLPNN, and 1D CNN. As shown in Figure.1, the SVM, MLPNN, PSO-MLPNN, and 1D CNN models achieved an accuracy values of 90.29%, 91.67%, 97.71%, and 98.28%, respectively. The deep learning model demonstrated superior accuracy, followed by PSO-MLPNN, MLPNN, SVM. Remarkably, the deep learning model exhibited a 7.99%, 6.81%, and 2.1% improvement in accuracy compared to SVM, MLPNN and PSO-MLPNN models, respectively.

Figure 2 visually depicts the efficacy of the developed models such as SVM, MLPNN, PSO-MLPNN, and 1D CNN. As depicted, the SVM yielded recall of 91.43%, MLPNN of 95%, PSO-MLPNN of 97.71%, and 1D CNN of 98.86%. Upon analysis, it became apparent that the 1D CNN model showed an improvement of 7.43%, 3.86% and 1.15% in recall compared to the SVM, MLPNN, and PSO-MLPNN models, respectively. The findings underscore the efficacy of the 1D CNN model in recalling instances relevant to conductive ink selection in PE applications and highlighting the importance of using sophisticated architecture for improved performance in complex tasks.

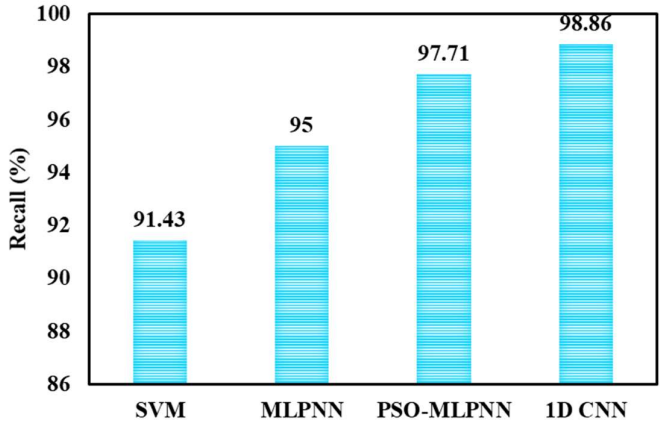

FIGURE .2 PERFORMANCE COMPARISON IN TERMS OF RECALL

Figure .3 provides a visual representation of the effectiveness of the developed models, namely SVM, MLPNN, PSO-MLPNN, and 1D CNN. It is observed from the Figure .3 that the SVM, MLPNN, PSO-MLPNN, and 1D CNN attained precision values of 81.22%, 92.68%, 92.93%, and 96.65%, respectively. This analysis exhibited that the 1D CNN model exhibited improvements in precision of 15.43%, 3.97% and 3.72%, respectively. The enhanced precision of the 1D CNN model highlights its effectiveness in accurately identifying relevant instances and contributing to its superior performance compared to the other methods.

Figure .4 depicts the efficacy of the models in terms of F1 score. Upon examining Figure .4, the SVM, MLPNN, PSO-MLPNN, and 1D CNN models achieved F1-score values of 86.02%, 93.83%, 94.74%, and 97.74%, respectively. This analysis highlights the noteworthy improvement in F1-score exhibited by the 1D CNN model, with enhancements of 11.72% 3.91 % and 3 % compared to the SVM, MLPNN and PSO-MLPNN.

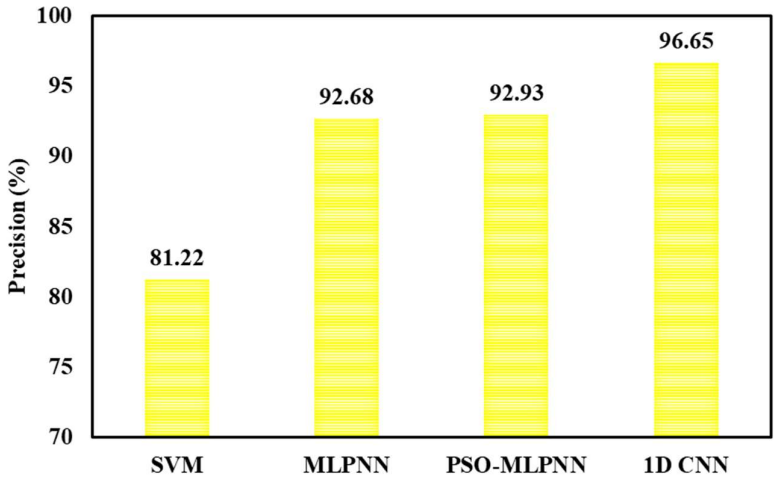

FIGURE .3 PERFORMANCE COMPARISON IN TERMS OF PRECISION

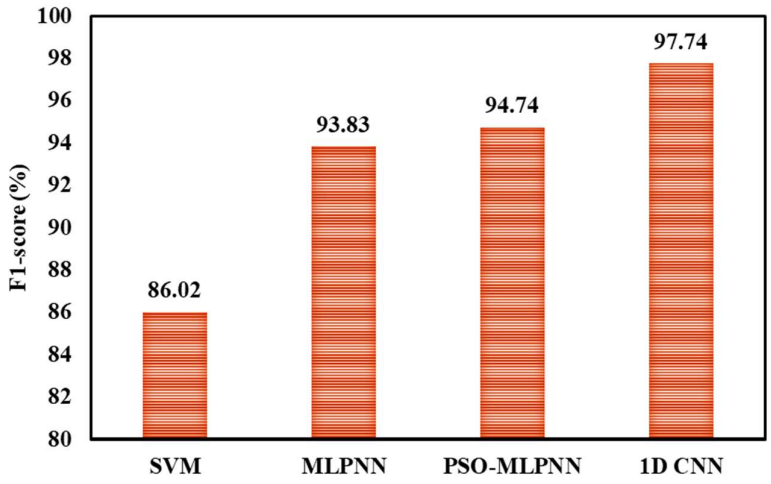

FIGURE .4 PERFORMANCE COMPARISON IN TERMS OF F1-SCORE

The performance of different models based on their BCR values is graphically compared in Figure .5. Upon analysing Figure .5, it can be observed that the SVM, MLPNN, PSO-MLPNN, and 1DCNN models yielded BCR values of 84.43%, 90.15%, 97%, and 98.57%, respectively. This assessment emphasized the significant increase in BCR value exhibited by the 1DCNN model, with improvements of 14.14%, 8.42%, and 1.57% compared to the SVM, MLPNN, and PSO-MLPNN.

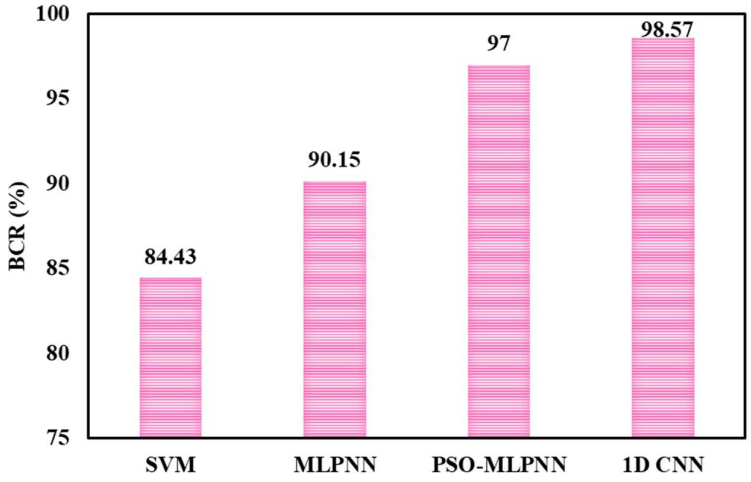

FIGURE .5 PERFORMANCE COMPARISON IN TERMS OF BCR

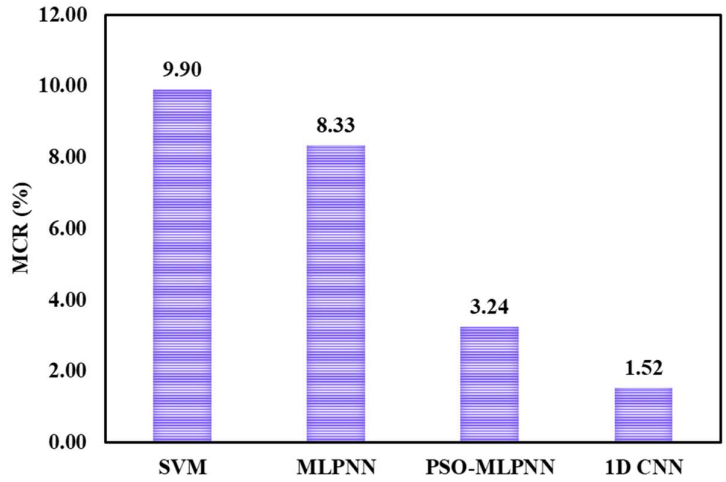

FIGURE .6 PERFORMANCE COMPARISON IN TERMS OF MCR

Pictorial representation of various models performance based on their MCR values is depicted in Figure .6. Analysis of the Figure .6 revealed that the SVM attained MCR value of 9.90%, MLPNN of 8.33%, PSO-MLPNN of 3.24%, and 1D CNN of 1.52%. The designed showed excellent performance by reporting lower MCR value compared to other models.

7. CONCLUSION

The emergence of novel materials with flexible and stretchable characteristics, coupled with advancements in processing technologies, have paved the way for the development of new connected devices and applications. PE stands out as a promising alternative to traditional electronic manufacturing processes. Three automated systems have been implemented to choose conductive ink for PE applications. In the first system, two networks, SVM and MLPNN were adopted to choose conductive ink. Results showed that the MLPNN gave better performance than SVM. In the second system, PSO-MLPNN was employed to select conductive ink for PE applications. Results demonstrated that the performance of the PSO-MLPNN model was superior to standard MLPNN across all metrics. In the third system, 1D CNN was adopted to conductive ink for PE applications. Performance of the model was analysed and compared with MLPNN and PSO-MLPNN. Results revealed that the 1D CNN model outperformed the MLPNN and PSO-MLPNN across all metrics.

8. ORGANIZATION OF THE THESIS

Chapter 1 gives an introduction about PE and its classification, screen printing, conductive inks, computational intelligence techniques, statement of problem, motivation, and

research objectives. **Chapter 2** discusses and analyses the earlier works which are related to this research work. **Chapter 3** explains the input and output variables considered and contribution of this research work. **Chapter 4** delineates the first contribution of search work such as automated conductive ink selection system for printed electronics applications. **Chapter 5** explains the second contribution of the research work such as optimized neural network for conductive ink selection in PE. **Chapter 6** describes the third contribution such as deep learning model for conductive ink selection in PE. **Chapter 7** analysis the complete performance analysis of the proposed methods. **Chapter 8** concludes the research work and provides the possibility of future work for further development.

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N. Alagusundari Dr.S. Sivakumari A novel optimized neural network model for ink selection in printed electronics" *International Journal of Electrical and Electronics Research" Volume no:11 No 4, pp.1103-1109 December 2023* (Scopus indexed)

N. Alagusundari Dr.S. Sivakumari A reliable and intelligent ink selection system for printed electronics using artificial neural network" *International Journal of Engineering Trends and Technology" Volume No: 72 No 1, pp.193-201 January 2024* (Scopus indexed)

N. Alagusundari Dr.S. Sivakumari Application of deep learning model for conductive ink selection in printed electronics" Advances in Science and Technology Research Journal" (submitted)

Book Chapters & Conference Proceeding

Book Chapter: Alagusundari, N, T.K.S. Lakshmi Priya, "3D Printing Techniques to Provide IT Solutions to the Challenges in Healthcare" in National Conference on "Digital India: Power to Empower", 22nd Sept 2017, Digitization for Transforming India, pg.8-14. Shanlax Publications, Madurai. ISBN: 978-93-87102-98-9.

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